# LSM Midterm Notes

*Nurmister*

## Contents



## 1 Introduction

This report pertains to the following UROPS project:

> Project number 17165: Application of Machine Learning Techniques to Automated Parking Lot Classification

The project is being undertaken by RAYAKAR ACHAL AJEET (A0156139B) in Semester II of Academic Year 17/18 and is being supervised by Vik Gopal from DSAP.

The initial task of this project was to train a convolutional neural network (CNN) to classify images of parking spots[1] from publicly available datasets. Having done so, the next part is to apply the techniques we learn to data gathered within NUS. The purpose of this write-up is to detail this application, with a focus on how we will protect data gathered within NUS.

The rest of this document is organised as follows: In section 2, we summarise the goals of the project. In section 3, we outline how we intend to collect the data from Faculty of Science, and how we intend to protect the data. In the conclusion, we outline the follow-up work that this project allows us to work on.

## 2 Project Goals

The search for parking spots adds to the tedium of commuting; current means of expediting search, such as occupancy level billboards outside parking lots, do not offer sufficiently specific information for the purpose of finding a spot quickly. We desire to enhance the specificity of occupancy information available to users through a machine learning-driven application. Ultimately, we aspire to establish the following workflow:

User requests for spot-wise occupancy status through the application,
↓
Picture of lot taken by a standard CCTV or dedicated camera,
and transmitted to associated *cloud-based deep-learning model*,
↓
Spots in picture classified as empty or occupied by model,
↓
Picture deleted, and user sent spatially-accurate abstraction of spot-wise occupancy status.

The emphasis is on utilising AI, based on low-cost images of parking spots, rather than an expensive implementation of sensors at every parking spot.

### 2.1 Choice of Machine Learning Tool

The deep-learning model aforementioned refers to a convolutional neural network (CNN). CNNs are a class of artificial neural networks, which are statistical models that are designed to fit complex nonlinear hypotheses to data and improve them iteratively and

[1] In this document, an individual parking space is referred to as a parking *spot*, and spots constitute a parking *lot*.

automatically. CNNs in particular are currently state-of-the-art in computer vision-related tasks; our task is one of binary image classification.

Before a CNN is ready for use in ascertaining the occupancy of a parking lot from its picture, it must be trained to do so. This training process requires a large number of *training examples* – namely, different pictures of the parkling lot which each have their spot-wise occupancy manually labelled. During the training process, the CNN will learn what aspects of the picture of a spot imply it is occupied or empty through relating the images to their labels. This training process can take several hours or days, depending on the number of training examples at hand.

After training, the CNN will be able to create predictions with an estimable level of accuracy. Per-image prediction is almost instantaneous.

### 2.2 Partial Proof of Concept

A large dataset concerning two parking lots, PKLot, is available through [1]. The dataset contains about 700,000 images of spots between the two lots, taken over a month. It is robust in the sense that it contains images from a wide range of light and weather conditions. Figure 1 contains sample images from these publicly available datasets.

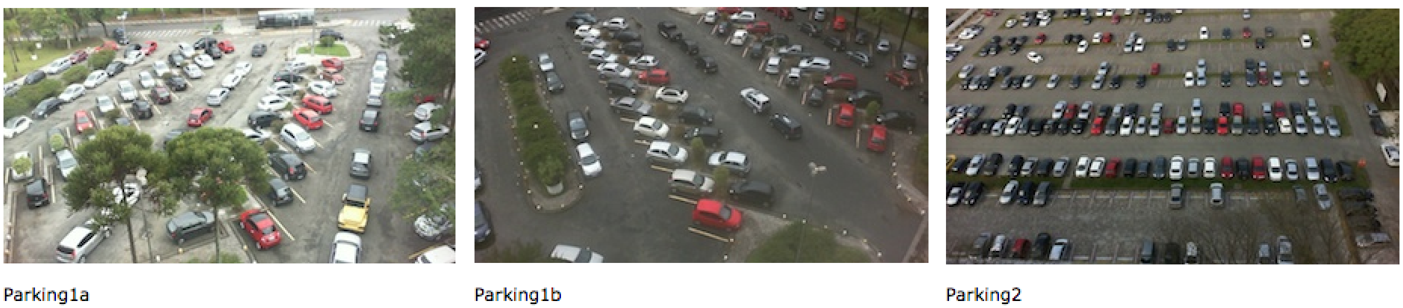


Figure 1: Images from publicly available datasets

We created a CNN for each of these parking lots, and achieved prediction accuracies of 99.8+%, which translated to the misclassification of about 260 spots in requesting for the prediction of the state of about 175,000. It is therefore without question that CNNs are apt tools for this task. It will be fruitful to understand how this success can be replicated in the local context, where we have control over collection of data.

## 3 Data Collection from NUS

The next phase in our study is to apply the knowledge to the local domain. In order to do so, we need to collect data from within NUS. This will allow us to practice the necessary skills to apply a model in practice, starting from data preparation, cleaning, and thence to model tuning for the specific context.

We initiated a discussion with Sulaiman Salim from the Office of Campus Amenities (OCA) in order to obtain permission to capture images of parking lots within NUS. They are interested in the project, and to see how else sensors can be used to solve other problems that they face, but they require us to think further about the privacy issues that could arise from capturing images of parking lots within NUS. The rest of this section details our proposed data collection procedure, and how we can minimise any intrusion and exposure of details of individuals and their cars.

### 3.1 Equipment, Location, and Frequency of Data Capture

We intend to use an Arduino Yun (an inexpensive microcontroller board with WiFi support), connected to a 720p USB webcam and a 64 GB microSD card to capture pictures of our selected lot. As soon as an image is captured, it will be encrypted using 256-bit AES (Advanced Encryption Standard) before being wirelessly uploaded to a private dropbox account. In addition, the encrypted version of the image will be written to the microSD for backup purposes. The encryption helps to protect against malicious individuals who attempt to steal the data from the physical device, or by hacking it's WiFi account. Regular logs will inform us if the data is being collected correctly or if something has gone wrong.

After discussing with OCA and doing some scouting of our own, we propose to perch the device at a vantage point overlooking the parking lot adjacent to Block S17 and the AYE. Figure 2 an image from the proposed vantage point, taken at 720p.

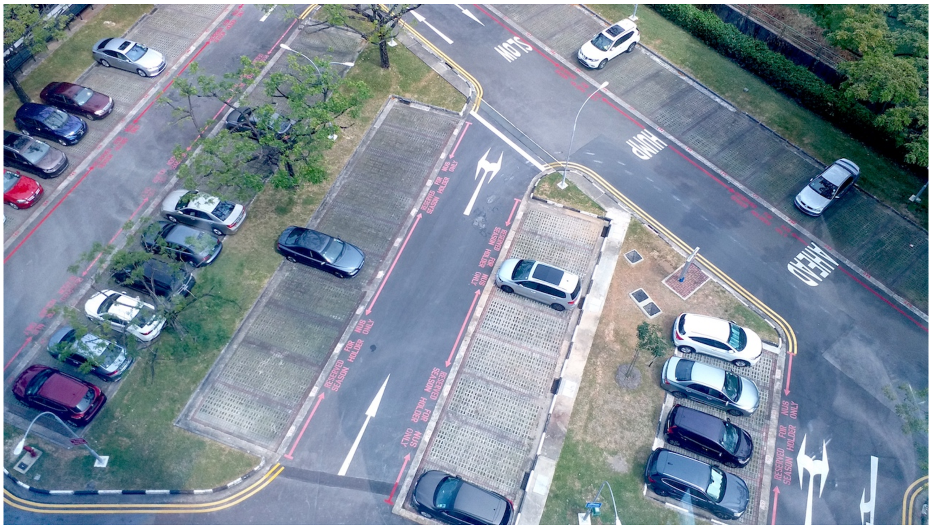

Figure 2: S17 parking lot

The exact location of the vantage point is the highest point of one of the stairwells in S17. It is explicitly identified by the orange circle in Figure 3

Figure 3: Proposed location of capture device

Judging from the sample pictures taken, the distance and resolution preclude identification of individual features or humans and identifiable characteristics of cars, such as their license plates. Thus we believe that the images themselves do not need to be edited or modified to further safeguard the privacy of individuals.

We propose to obtain approximately 200,000 images of parking spots. This is of the same order as the publicly available dataset, and is what allowed us to achieve the observed level of accuracy. Based on the number of parking spots in the images above (approximately 50), we would be able to achieve our target if we capture images at five minute intervals, every daylight hour, for four weeks.

When the observational period is over, all images will be downloaded and then secure deleted from the microSD card and DropBox account.

### 3.2 Training the CNN, in the Cloud.

Training and configuration of CNNs will be done online on Floydhub, which means that we will ultimately be storing all collected image data on a private repository on the cloud. These images will stay there until this project culminates, likely in August 2018. There are a number of reasons for these choices:

1. The Python machine learning library that we use, TensorFlow, is set up and updated automatically for us on FLoydhub along with all dependency modules.
2. Great computing power is available on the cloud inexpensively; it will save us many hours in training.

3. Training multiple configurations of the same CNN concurrently is possible – on a personal computer, it is not. Again, time will be saved.
4. Working on the cloud allows all involved in the project to collaborate seamlessly, and is the norm in industry.
5. Moving development to the cloud will better prepare us to serve the model to users in future.

We have queried Floydhub regarding their security practices in order to satisfy our concerns that it could be a point of weakness in our workflow. Floydhub is hosted on AWS; they too use 256-bit AES to communicate with local machines to run jobs. They have taken measures to restrict the number of users (to just two) who have administrative access to their servers. Finally, user passwords and authentication tokens are not managed by them, but by Auth0. We believe this is more than sufficient for our application and data.

## 4 Conclusion and Extensions

Increasing the resolution of information available to those seeking a parking spot is not the only implication of this project, especially given that NUS' parking lots are organized appropriately for demand. Rather, we truly view this project as a capability-building exercise; a segue into greater problems that can be addressed by machine learning – either by us or those who take reference to our experiences in the future. For instance, even in the context of this application, there are several extensions that we could consider:

1. How well can we classify the lots using grayscale images, which is typically what we obtain from CCTV cameras?
2. How well can we classify lots at night?
3. How can we overcome occlusion due to trees or neighbouring large cars?
4. How well can the model perform this task indoors? How extensive a network of cameras would be needed in such a case?

## References

[1] Paulo RL De Almeida, Luiz S Oliveira, Alceu S Britto Jr, Eunelson J Silva Jr, and Alessandro L Koerich. Pklot–a robust dataset for parking lot classification. *Expert Systems with Applications*, 42(11):4937–4949, 2015.